ASSESSMENT OF THE IMPACT OF A DISRUPTOR ON THE COMMUNICATION ENVIRONMENT

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Abstract. In today's world, where the volume of information is constantly growing, effective communication is a key element of success in object-oriented organizations, especially those that use virtual teams, so identifying communication problems is important. To improve the quality of the analysis of communication processes, it is proposed to use a neural network. The scheme of this network is presented in the document. The network was trained on the DisRating dataset, which was developed based on the evaluation of the organization's data, and demonstrated high classification efficiency, which was determined using a series of analytical graphs. The results were analyzed using graphs (Bias histogram, Kernel histogram, Change of losses Mean Absolute Error). Based on the initial data of the network with the help of GAP analysis, the quantitative impact on individuals in the field of communication was determined. A model for quantitative assessment of the disruptor impact on the communication environment is presented. The proposed approach achieved high accuracy in the tasks of identifying the areas of the disruptor influence and its evaluation.

Keywords. Communications, convolutional neural network, project-oriented organization, disruptor, machine learning**.**

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INTRODUCTION

The ability to automatically identify communication problems can significantly improve performance in project-oriented organizations [1], especially in case of using virtual teams. This can increase the competence of both the virtual team and the organization as a whole [2]. Analysis of communications using neural networks can be a useful tool for identifying individuals with certain communication problems. In [3] research was conducted on the analysis of textual data in a project-oriented organization. As a result, we received a set of data where it was determined how many times a person intervened in the communication process. However, after receiving such data, it is necessary to evaluate it, because the information needs additional analysis in its current form. Such an analysis is also proposed to be carried out using a neural network.

Article presents the performance of a neural network built using the TensorFlow open-source machine learning software library. Such neural networks are known for their ability to numerically evaluate data. The purpose is to develop a model to determine how a person numerically affects the communication process within the text (analysis of documents, letters, messengers). A new data set based on internal communications within the organization called DisRating was created for development and evaluation. The DisRating dataset was split into a training dataset and a validation dataset. The training dataset contains 70% of the records for model training, and the validation dataset contains 30% of the records for model analysis.

I. THE PURPOSE OF THE WORK

The aim of the study is the quantitative calculation of the disruptor impact on the communication environment. This article provides an overview of previous research in the field of deep learning classification algorithms, including convolutional neural network and others. The presented model implements various methods of evaluation and application of the neural network to obtain the best result.

Let's review the key steps and techniques used in neural networks to evaluate numerical data. Neural networks for the purpose of evaluating numerical data are widely used in regression, classification, time series forecasting and other numerical tasks. Here are the main types of neural networks and their applications for numerical data:

Multilayer Perceptron [4, 5] (MLP). This is the most basic type of neural network used for regression and classification. It consists of one or more hidden layers, each of which contains several neurons. Uses activation functions such as ReLU for non-linear data transformations.

Convolutional Neural Networks [6, 7] (CNN). Usually used for image processing, but can be used for numerical data, especially in tasks involving time series or spatial data. Use packages to capture local features of the data.

Recurrent Neural Networks [8] (RNN). Particularly useful for processing sequential data such as time series. RNN variants such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) are often used to improve the model's ability to remember long-term dependencies.

Graph neural networks [9] (Graph Neural Networks, GNN). Used to work with graph data structures, such as social networks, molecular structures, and other tasks where data can be represented as graphs.

The analysis of neural networks to evaluate numerical data is an important aspect of machine learning and is widely used to solve regression, classification, time series forecasting, and other problems. After all, neural networks are powerful tools for evaluating numerical data due to their ability to model complex nonlinear relationships. Python and the Keras, TensorFlow libraries were used to build a neural network that evaluates numerical parameters on a 10-point scale where a specific numerical input is mapped to a target rating. The development environment is Jupiter.

For training, I used my own data set, which was formed based on the classification of texts obtained from my previous research. Such a data set was called DisRating. It has such values as Id (id), Communication barriers (CBi), Resistance to change (RCi), Negativity (Ni) Micromanagement (Mi), Inaccurate information (IIi), Lack of collaboration (LCi), Dominating conversations (DCi), Time dilation (Ti) and Rating (R) [2].

The data is divided into training, validation and testing sets - 70%, 15%, 15% respectively.

Data normalization is necessary for the efficient operation of neural networks. The early stop used in the work helps prevent overfitting by stopping training when the loss of validation stops improving.

The scheme of such a neural network is shown on Figure 1. So, the scheme shows data with input values and corresponding estimates. Normalization of the input data is performed to improve the performance of the neural network. The model contains an input a layer with 8 neurons, two hidden layers and an output layer with 8 neurons (one for each evaluation).

The model is trained on training data and validated to prevent overtraining, evaluated on test data, and predictions are made for new input values.

This approach allows simultaneous evaluation of several values on a 10-point scale using a neural network, which simplifies the process of further processing of the output values.

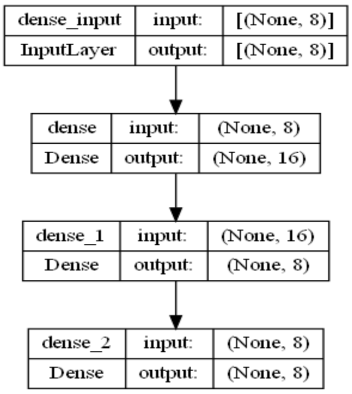

Figure 1. Neural network diagram

This neural network was analyzed in a number of ways. This is a bias histogram, so, in neural networks, it provides useful information about the distribution of bias values in the layers of the network. Analysis of these histograms helps to understand how neurons are tuned and how they interact with weights and activations. Learning diagnostics help identify problems with initializing or updating offsets. Optimizing the model allows to understand which layers need more fine-tuning. Analysis of activations helps to see which neurons are actively used.

The interpretation of displacement histograms consists in the distribution of displacements - the histogram shows the distribution of the displacement values of each layer of the network. This is useful for understanding how eliminations change during learning.

Analysis of the histograms in the early stages of training can help assess whether the eliminations are initialized correctly.

The elimination histograms, shown on Fig. 2, [10] help diagnose and optimize the model by providing visual information about the distribution and change of shifts during training.

The default analysis method is kernel density estimation (KDE) (see Fig. 3) - applying kernel smoothing to estimate probability density, i.e., a nonparametric method for estimating the probability density function of a random variable based on kernels as weights. KDE solves the fundamental problem of data smoothing, where inferences about a population are made based on a finite sample of data. In some fields, such as signal processing and

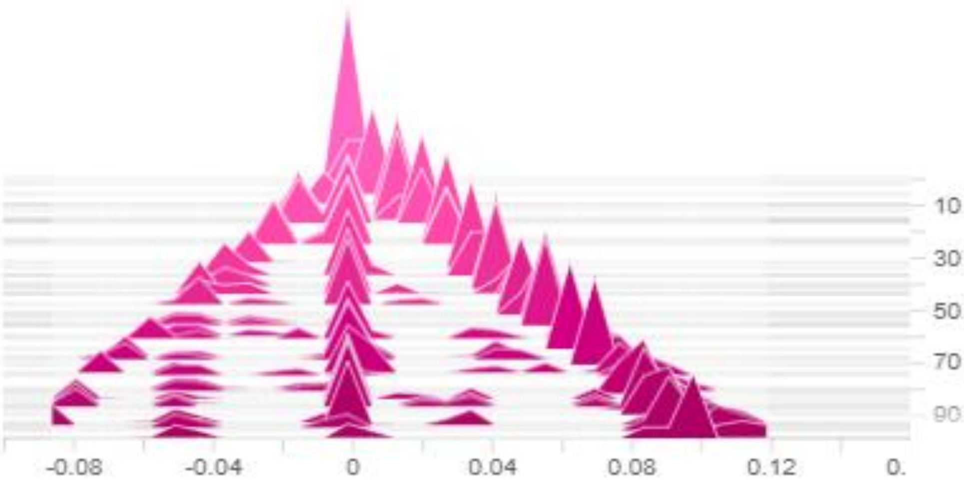

Figure 2. Elimination histograms

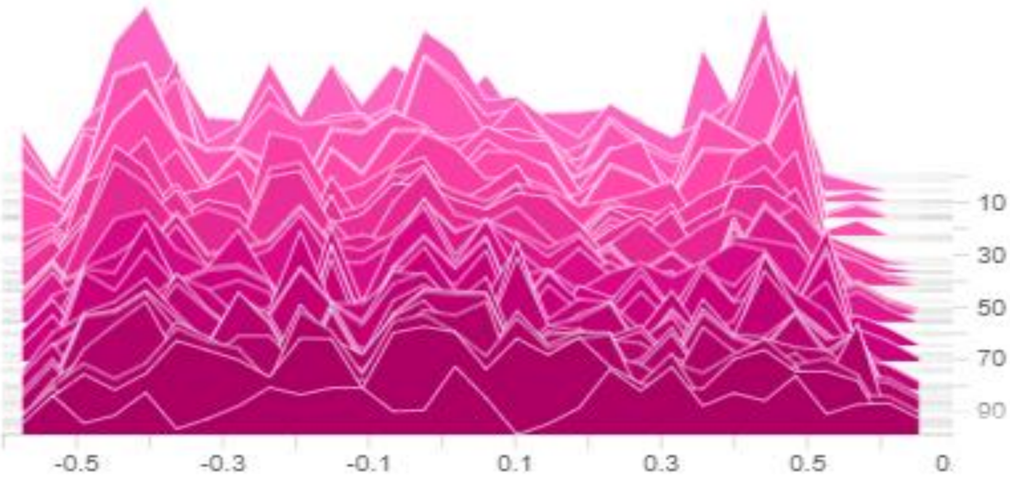

Figure 3. Kernel density estimation histogram

econometrics, it is also called the Parzen–Rosenblatt window method after Emanuel Parzen and Murray Rosenblatt, who are generally credited with independently creating the method in its current form [11, 12]. One of the well-known applications of kernel density estimation is the estimation of the marginal density of data, determined by a class, when using a naive Bayes classifier, which can improve the accuracy of the prediction [13].

The loss graph, shown on Fig. 4 on the left side, is an important tool for analyzing the learning process of a neural network. It shows how the value of the loss function on the training and validation data sets changes as each training epoch passes [14]. This helps to understand how well the model is learning and whether it has problems with overtraining or undertraining.

The construction of this graph was implemented using the TensorFlow library and its TensorBoard visualization.

A decrease in loss on the training data set indicates that the model is successfully trained and minimizes the error. The reduction in loss on the validation set shows that the model also performs well on unseen data.

This graph shows how the loss on the training and validation data sets changes as each epoch passes. The construction and analysis of the epoch loss plot is an important part of the neural network training process. It helps to understand how the model learns and to detect problems with overtraining or undertraining. Regular monitoring of this graph allows you to make informed decisions about tuning hyperparameters and improving the model.

The graph of the change of losses (loss) by iteration is also a useful tool for analyzing the learning process of a neural network. It allows

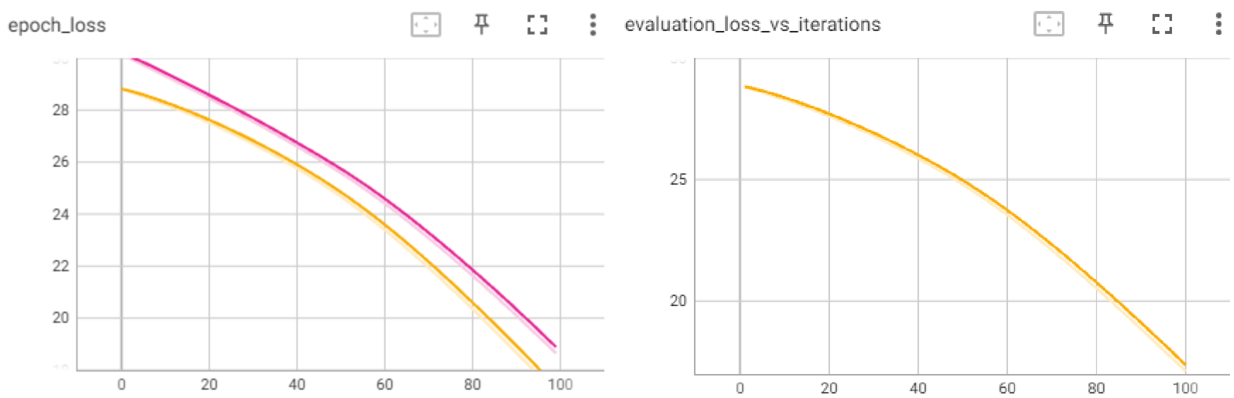

Figure 4. Change of losses by iteration

you to visualize how the loss function changes during training and helps you understand how effectively the model learns on training and validation data. Consider such a graph using the TensorFlow library, shown on Fig. 4 on the right side.

A decrease in loss on the training data set indicates that the model is successfully trained and minimizes the error on the training data. The reduction in loss on the validation set shows that the model also performs well on unseen data. If the loss on the validation data set starts to increase, while on the training data set it continues to decrease, this may indicate that the model is overtrained.

Thus, the loss plot by iteration helps to understand how the model is learning and to identify problems with overtraining or undertraining. Regular monitoring of this graph allows you to make informed decisions about tuning hyperparameters and improving the model.

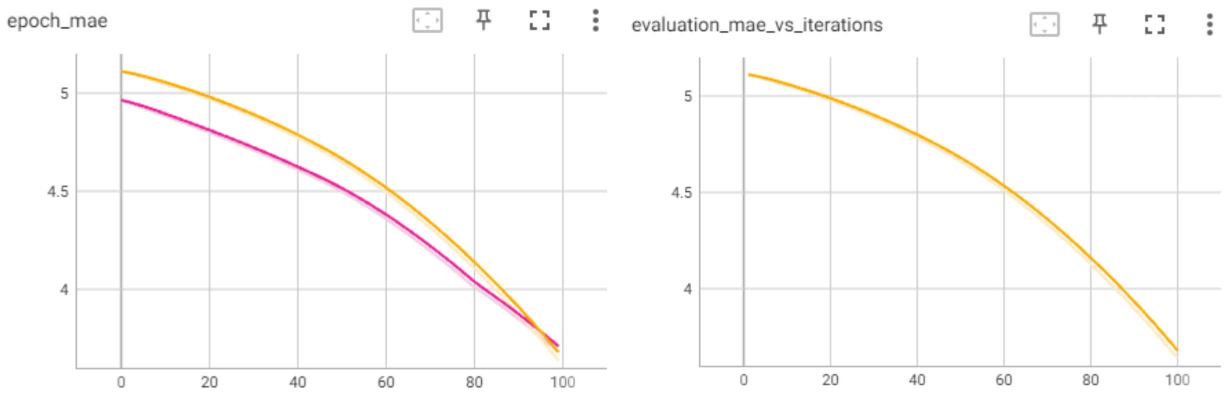

Figure 5. Mean Absolute Error plot by epoch

The MAE (Mean Absolute Error) plot by epoch (see Fig. 5) shows how the mean absolute error on the training and validation data sets changes as each training epoch passes [15]. This helps to analyze the learning process of the model and evaluate its performance. A decrease in MAE on the training data set indicates that the model is successfully trained and minimizes the mean absolute error. The decrease in MAE on the validation set shows that the model also performs well on unseen data.

Data set divergence means that if the MAE on the validation data set starts to increase while the training data set continues to decrease, this may indicate overtraining of the model [16].

Plotting and analyzing the MAE plot by epoch is also an important part of the neural network training process. It helps to understand how the model learns and to detect problems with overtraining or undertraining.

The MAE (Mean Absolute Error) graph by iterations helps to visualize how the mean absolute error changes on the training and validation data sets as each training iteration passes. This allows for a better understanding of the model's learning process and its ability to generalize on unseen data.

A decrease in MAE on the training data set indicates that the model is successfully trained and minimizes the mean absolute error on the training data. The decrease in MAE on the validation set shows that the model also performs well on unseen data.

Divergence of MAE on the training and validation datasets: If the MAE on the validation dataset starts to increase while the training dataset continues to decrease, this may indicate overtraining of the model. This graph shows how the MAE on the training and validation datasets changes as each iteration progresses. Plotting and analyzing the MAE plot over iterations helps you understand how the model is learning and identify overtraining or undertraining problems.

After each individual's area of influence has been assessed, it is necessary to determine how quantitatively it affects communication in virtual teams in general. For this, we will use GAP analysis [17].

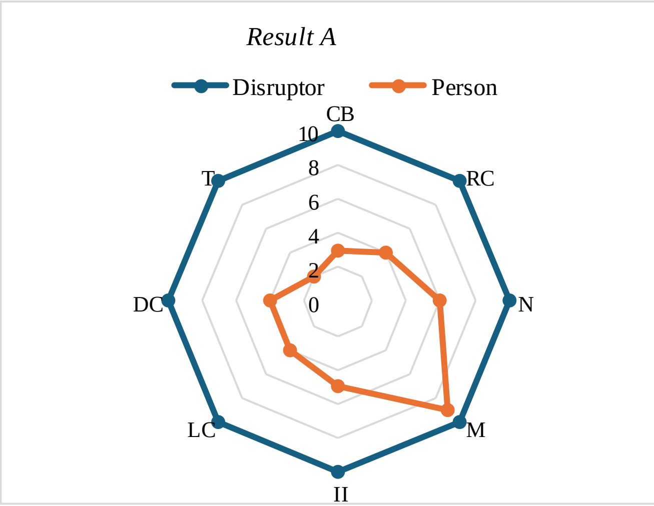

Figure 6. GAP analysis to evaluate disruptor

Creating a gap analysis diagram involves visualizing the current state versus the desired state, identifying the gaps, and outlining steps to close those gaps. Here is the basic structure for a gap analysis chart:

1. Domains of focus. Areas of influence of communications will become measurements.

2. The current state is described using the evaluation determined by the neural network for each dimension.

3. Target state. Our task is to find a disruptor, so the target state will be described by the maximum value for each of the dimensions

4. Identified gaps. It is necessary to calculate the differences between the current and desired states. Make necessary adjustments to strategies and actions based on feedback and results.

The chart, shown on Fig. 6, serves as a clear and structured way to visualize gaps and plan action steps to achieve desired results.

So, based on such an analysis, we can assess exactly how quantitatively the disruptor affects the areas of communication. We can determine that if all areas of influence are rated at 10, this means that the person has the maximum destructive influence of all possible. Then we will analyze the data on a specific person obtained with the help of our neural network. To find how much a person violates communication, one should equate his current violation with the maximum possible. For a quantitative assessment, it is suggested to calculate the areas of these figures, and to find out what percentage of the person's influence area is from the maximum influence.

To calculate the area of the figures shown in the diagram, we will use known methods for calculating the area of a regular polygon and an irregular polygon, if the coordinates of the vertices are known. A radial chart displays values as a polygon with vertices whose values can be determined.

Determination of the coordinates of the vertices: the central polygon has 8 vertices. The diagram contains two polygons: outer (blue) and inner (orange).

Calculation of coordinates: The coordinates of each vertex can be obtained using polar coordinates (radius and angle). The central polygon has vertices corresponding to values on each axis. Calculating the area: We use the formula for the area of a polygon based on the coordinates of its vertices. Let's calculate the area of the polygon for the values on the axis.

External polygon (Disruptor): Axis values: CB: 10 RC: 10 N: 10 M: 10 II: 10 LC: 4 DC: 10 T: 10

Inner polygon (Person):
Axis values: CB: 3 RC: 4 N: 6 M: 9 II: 5 LC: 4 DC: 4 T: 2

The formula for the area of a polygon:

$$A = \frac{1}{2}\left|\sum_{i=1}^{n}(x_i y_{i+1} - y_i x_{i+1})\right|$$

For each polygon, we will substitute the coordinates in the formula and calculate the area. The areas of the figures on the radial diagram:

• The outer octagon (maximum values on each axis) has an area of approximately 282.84 square units.

• The inner octagon (values on each axis) has an area of approximately 65.41 square units.

Now let's find out the ratio of the actual disruptor to the complete one. Through simple calculations, it was determined that it is 22,7%.

So, based on these calculations, we can say that a person has a managerial influence on 22,7% of the communication environment. This indicator is proposed to be used to assess communication problems.

CONCLUSIONS

To enhance the quality of communication process analysis, a neural network is proposed. The architecture of this network is detailed in the document. This neural network was trained on the DisRating dataset, which was specifically developed based on the organization's communication data. It was divided into educational and training areas. The network demonstrated high classification efficiency, confirmed through a series of analytical graphs.

Training and Evaluation Process. The network's performance was evaluated using various graphical analyses: Bias Histogram: Showed the distribution of biases in the network, indicating how well the model generalizes. Kernel Histogram: Illustrated the distribution of weights in the network layers, highlighting areas of focus. Loss and Mean Absolute Error (MAE) Graphs: Tracked changes in loss and MAE over the training epochs, demonstrating the model's learning progress.

Quantitative Impact Analysis. Using the initial data from the network, a GAP analysis was conducted to determine the quantitative impact on individuals in the communication domain. The analysis provided insights into how different factors affect communication processes and identified key disruptors.

Model Presentation. The model developed for the quantitative assessment of disruptors' impact on the communication environment is detailed. This model can accurately identify the areas of influence of disruptors and evaluate their effects.

Results and Accuracy. The proposed approach achieved high accuracy in identifying the influence areas of disruptors and in evaluating their impact. The results validate the effectiveness of the neural network in improving communication process analysis.

This comprehensive method offers a significant advance in the understanding and management of communication in organizations, especially those using virtual teams, providing a reliable tool for identifying and mitigating communication problems.

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Оцінка впливу руйнування на комунікаційне середовище

Владислав КОНЦЕВИЙ

Анотація: Стаття розглядає зростаючі виклики комунікації в об’єктно-орієнтованих організаціях, зокрема тих, що використовують віртуальні команди, пропонуючи підхід на основі нейронної мережі для аналізу та вдосконалення комунікаційних процесів. Представлена детальна схема нейронної мережі, навченої на наборі даних DisRating, розробленому на основі організаційних оцінок, що демонструє високу ефективність класифікації. Аналітичні графіки, такі як гістограми зміщення та гістограми ядра, були використані для підтвердження результатів, поряд із показником середньої абсолютної похибки для оцінки втрат. Використовуючи аналіз GAP, дослідження було кількісно оцінено вплив руйнівників на динаміку зв’язку та запропонувало модель для оцінки цих впливів. Цей підхід досяг значної точності у визначенні зон впливу руйнівників, запропонувавши багатообіцяюче рішення для покращення аналізу комунікацій у складних організаційних середовищах.

Ключові слова: комікації, згорточна нейронна мережа, проєктно-орієнтована організація, диспаратор, машинне навчання